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ABSTRACT

Two studies that compare the use of analysis of patterns in time (APT) (formerly non-metric temporal path analysis) and the linear models approach (LMA) are reported. In the first study, scores on the College Entrance Examination Board French Achievement Test (CEEBFAT), number of years of study of high school French (YHSF), and course achievement points (CAPs) of 87 undergraduate students at Indiana University (Bloomington) were analyzed. The 87 subjects were placed in one of three different levels of French courses. A linear regression analysis was conducted with placement test score (PTS) and YHSF as predictor variables and CAPs as the dependent variable. APT was subsequently used in data analyses. The LMA-predicted probabilities were compared to APT probabilities using the chi-square goodness-of-fit test. In the second study, a hypothetical data set was constructed in which CAP was not correlated with YHSF and PTSs; thus, the data set lacked linearity. Both the actual and hypothetical data sets had the same number of subjects in each corresponding PTS category/YHSF block. LMA and APT analyses were conducted on this hypothetical data set as in the first study. The results of these two studies show that APT is a more powerful tool than LMA in analyzing data with no inherent linear or deterministic relations. APT probabilities retain more specific information in the data by not averaging data across levels of various variables, as in LMA. APT is thus a better tool for analyzing stochastic educational processes. However, the results fail to illustrate a very important component of APT--temporal sequencing. Nine data tables are included. (RLC)

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A Comparison of Nonmetric Temporal Path Analysis with Linear Models Approach Using Actual and Hypothetical French Placement Data

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Abstract

The name nonmetric temporal path analysis was recently changed to analysis of patterns in time (APT). APT was used to analyze actual French placement data of eighty-seven undergraduate students and hypothetical French placement data of eighty-seven subjects. It was found that APT was more adequate than the linear models approach (LMA) in analyzing data which lacked an inherent linear relationship. Hence, APT is a more appropriate analytical tool for stochastic processes than LMA. The present paper also suggests that APT, coupled with Bayesian reasoning, can be considered as a general system approach to educational measurement. A system can become more "intelligent" as a result of Bayesian or Bayesian-like updating of APT results.

Introduction

A statistical approach that is widely used in educational research is the linear models approach (LMA), which includes statistical methods like multiple regression analysis, ANOVA, etc. Underlying the LMA is a deterministic assumption that each initial state of a system is associated with one and only one posterior state. Implicit also in the LMA is the assumption that variables can be independently measured and their relations can be described by some linear equation. However, there has been concern that many cognitive and system processes, including many educational processes, are not deterministic (Anderson et al., 1984; Lincoln and Guba, 1985). Rather, they are often stochastic processes, in which an initial state is associated with two or more posterior states; and often they cannot be accurately or adequately described by linear mathematical equations.

Nonmetric Temporal Path Analysis

Frick (1983) developed a nonmetric temporal path analysis (NTPA) for stochastic relations. To avoid possible confusion, it should be noted that NTPA bears no relation to traditional path analysis. The name nonmetric temporal path analysis is used because it is a logical description of the conception of the methodology. More recently, Frick (in press) has changed the name to Analysis of Patterns in Time (APT). However, it is only the name which has been changed, not the methodology. In what follows, APT will be used in place of NTPA.

Analysis of Patterns in Time

In APT, a classification is defined as a set of mutually exclusive and exhaustive categories. Every classification must include a NULL category, which is used when nothing relevant to the classification is observable. For example, traffic light color—{red, yellow, green, NULL}—is a classification, and red is one category.

A nonmetric temporal path in APT is a mapping of observed events or states of affairs into relevant categories of classifications. More generally, a nonmetric temporal path can be conceived as a process or pattern indicating some relation among several events or states of affairs. As the classification into which observed events are mapped can be virtually any set of mutually exclusive and exhaustive categories (that is, the classification need not be a set of integers or rational numbers), a mapping does not have to involve assigning a numerical value to an event and hence a path is nonmetric. In addition, since a mapping involves simultaneity and temporal order of occurrence of events, a path is temporal.

APT measures the strength of relation between observed events in terms of the probability or duration of occurrence of a relevant nonmetric temporal path. In APT, systematic observation of a system is the mapping of events relevant to some classification of interest into their respective categories as they are observed to occur in time and in the system. An example of a system is an individual student.

APT hypotheses are specified as nonmetric temporal paths in the form of queries. A query is a question about the frequency or duration of occurrences or patterns of occurrences. For example, "If taste is sweet, then mood is good and friends are good, then humor is dry?" is a query. A query is made up of one or more phrases. A phrase is the occurrence of a singular event or the occurrences of several events. The logical operators, 'AND', 'OR', and 'NOT', can be used in a query phrase. Thus, there can be more than one classification in a phrase. Results of queries are estimated probabilities (relative frequencies, or relative duration, or both) of the system's paths or processes. It should be noted that the results (relative frequency and duration measures) of observation of a nonmetric temporal path are metric, but the relation (the path itself) is nonmetric.

APT does not preclude generalizations across systems of a given type. In fact, if systems are independent and are sampled with appropriate sampling techniques, probability measures of a particular nonmetric temporal path from observations of each system can be averaged. Descriptive and inferential statistics for a specified nonmetric temporal path can be derived from extant statistical and inferential procedures. Note that the unit of analysis on which population statistics are based is the probability measure of the specified path in each individual sampled system.

APT is limited to description of nonmetric temporal paths (patterns). It does not attempt to explain why the observed

paths occur, nor does it assume a one-to-one correspondence between category changes in one classification and category changes in another classification. In other words, there is no assumption in APT that relations have to be deterministic. It is thus an appropriate tool for studying stochastic processes. In fact, APT assumes the existence of stochastic processes and also the dependency of the current transition on prior transitions in the system. This, incidentally, coincides with the idea that "the present contains the past, but the present is not determined by the past" (Anderson et al., 1984, p.18).

The present paper reports two studies which were conducted in an attempt to compare the use of APT and LMA. In the first study, actual French placement data were used; in the second study, hypothetical French placement data were used. It was hypothesized in the two studies that APT would be more appropriate for analyzing data which lack linearity.

Study 1

Method

Scores on the College Entrance Examination Board (CEEB) French Achievement Test, years of study of high school French (YrHSF), and course achievement points (CAP) of 88 undergraduate students at Indiana University (IU) were collected. However, one student had miscoded his YrHSF, so his record was dropped from the study. Consequently, only 87 subjects were included in the study. The CEEB French Achievement Test is currently used by the French Department of IU as a placement test. The 87 subjects

were placed in one of three different levels of French courses (F100, F150, and F200). All 87 subjects were taking their first French course at IU.

At the time of data collection, LMA was intended to be the principal method of analysis. A linear regression analysis was carried out with placement test score (PLCS) and YrHSF as predictor variables, and CAP as the dependent variable. It was later decided to use APT to analyze the data. APT queries in this study were of only one type: "If YrHSF is *a* and PLCS is *b*, then CAP is *c*?" Due to combinatorial explosion, PLCSs and CAPs were collapsed into categories for APT queries; that is, *b* and *c* were categories. PLCS categories (PLCC) were based on cutoff scores now used by the IU French Department for placement into the above three French courses. There were three PLCC, namely, F100, F150, F200, which correspond to PLCS ranges of 200-430, 440-470, and 480-520, respectively. There were five CAP categories, namely, A, B, C, D, F, which corresponded to CAP ranges of 90-99, 80-89, 70-79, 60-69, and 1-59, respectively.

APT gives the probability of a CAP category after the observation of a particular PLCC and YrHSF. For example, among the 87 subjects in this study, there were 16 who had 3 YrHSF and who were then placed in F150, and out of these 16 subjects, 8 got an A from the course (see Table 2). The result of the APT query, "If YrHSF is 3 and PLCC is F150, then CAP is A?" was therefore 0.5.

APT probabilities can be more meaningful if they are reported together with confidence intervals. If there is no reason to believe that the APT probabilities of interest form a non-normal distribution, then the confidence interval of an APT probability can be computed by treating all categories of a classification other than the category of interest in the last phrase of a query as one single category. For example, all CAP categories other than A in the above query can be collapsed into a single non-A category. Since there was no prior reason to believe that APT probabilities in this study did not form a normal distribution, confidence intervals for APT probabilities were computed according to one of the following formulae (Kirk, 1984):

$$p \pm (z*\mathrm{sqrt}(pq/n)) \qquad (1)$$

$$p \pm ((1/(2n)) + z*\mathrm{sqrt}(pq/n) \qquad (2)$$

where p = observed sample proportion

q = 1-p

z = z score corresponding to the desired α level of significance.

Formula (1) was used when both np and n(1-p) were greater than 5. Otherwise, formula (2) was used.

The uses of APT and LMA were compared by first forming a 0.95 confidence interval of the observed mean CAP for a particular PLCC/YrHSF block according to the following formula (Glass & Hopkins, 1984):

$$\bar{X} \pm {}_{.975}t_{v}s_{\bar{x}} \qquad (3)$$

where $\bar{X}$ = observed mean CAP

v = (number of subjects) - 1

A LMA-predicted CAP range was then determined by computing the predicted CAP for the highest and the lowest PLCSs of the PLCC/YrHSF block from the linear regression equation. If the confidence interval did not contain or overlap with the LMA-predicted CAP range, then non-linearity was assumed and APT should be used to reveal specific patterns in the data.

In our example above, the mean CAP of the 16 subjects was 88.06 (or a B). The 0.95 confidence interval of CAP was 84.85 to 91.27 (see Table 3). The regression equation predicted 85.35 and 86.10 CAPs for PLCSs of 440 and 470 (the lowest and highest PLCSs for F150 placement) respectively, given 3 YrHSF. Since the 0.95 confidence interval contained the LMA-predicted CAP range, APT and LMA yielded consistent results for this particular PLCC/YrHSF block.

The regression equation mentioned above used PLCS instead of PLCC as a predictor variable for two reasons. First, it is a common practice to use interval or ratio data, if available, instead of nominal or ordinal data in regression analysis. Second, inclusion of PLCS in the regression would mean making use of more information in the data, thus resulting in more precise prediction of CAP subsequently. One would be more convinced of using APT in place of LMA if it could be demonstrated that LMA

could not adequately describe the data set even when it was making its "best" predictions.

Frick (personal communication) suggested one way of comparing APT probabilities with LMA-predicted probabilities of CAP categories. Consequently, a second linear regression analysis was performed using YrHSF as a predictor variable and two dummy variables for the three PLCCs. The resulting regression equation was used to predict the mean CAP for subjects in a particular PLCC/YrHSF block. Assuming a normal distribution of CAPs in each PLCC/YrHSF block, the LMA-predicted mean CAP would be the mean of this normal distribution and the standard error of estimate from the regression analysis would be the standard deviation of that distribution. Based on such a normal distribution, LMA-predicted probabilities of the various CAP categories were determined for each PLCC/YrHSF block. This was done by converting the cutoff CAPs (i.e. 60, 70, 80, and 90) to z-scores on the normal distribution in a PLCC/YrHSF block. The z-scores partitioned the normal curve into five parts. The area of each part under the normal curve was the LMA-predicted probability of the corresponding CAP category.

The LMA-predicted probabilities were compared with APT probabilities using the chi-square goodness-of-fit test (Glass & Hopkins, 1984). Because of the small number of subjects in each PLCC/YrHSF block, CAP categories D and F were collapsed into one category so that the degree of freedom for the X^2 statistic was equal to one and Yate's correction could be applied. Yate's

correction is applicable only when the degree of freedom for X^2 is equal to one (Hays, 1981). It is legitimate to combine categories with small expected frequencies in the X^2 goodness-of-fit test (Snedecor & Cochran, 1989).

Results

Table 1 shows the APT results. Table 2 shows the distribution of grades, the means and standard deviations (S.D.) of CAPs for various combinations of PLCC and YrHSF categories. A regression analysis using PLCS and YrHSF as predictors of CAP was conducted. The resulting regression equation and standard error of estimate are shown at the bottom of Table 2.

The regression equation in Table 2 was used to compute the LMA-predicted CAP range for each PLCC/YrHSF block. Table 3 shows the LMA-predicted CAP ranges and the corresponding 0.95 confidence intervals of observed mean CAPs. Every confidence interval in Table 3 either contained or overlapped with its corresponding LMA-predicted CAP range, indicating linearity in the data and so LMA is a viable analytic tool in this case. The linearity in the data was also reflected by the significant intercorrelation between PLCS, YrHSF, and CAPs (see Table 4-A).

Table 5 shows the observed APT probabilities and LMA-predicted probabilities of CAP categories. The regression equations at the bottom of Table 5 resulted from a regression analysis with two dummy variables for PLCC. The X^2 goodness-of-fit test did not indicate any significant differences between the

APT and LMA probabilities. This was expected given the linearity observed in the data.

Table 1

APT Probabilities (Actual Data Set)

PLCC	YrHSF	APT Probability	
F100	1	P(A) - Not observed	P(B)=50.00 ± 94.30%
		P(C)=50.00 ± 94.30%	P(D) - Not observed
		P(F) - Not observed	
	2	P(A)=33.33 ± 36.35%	P(B)=33.33 ± 36.35%
		P(C)=22.22 ± 32.72%	P(D) - Not observed
		P(F)=11.11 ± 26.09%	
	3	P(A)=33.33 ± 70.01%	P(B)=66.67 ± 70.01%
		P(C) - Not observed	P(D) - Not observed
		P(F) - Not observed	
	4	P(A)=50.00 ± 61.50%	P(B)=25.00 ± 54.94%
		P(C) - Not observed	P(D)=25.00 ± 54.94%
		P(F) - Not observed	
F150	2	P(A)=20.00 ± 45.06%	P(B)=60.00 ± 52.94%
		P(C)=20.00 ± 45.06%	P(D) - Not observed
		P(F) - Not observed	
	3	P(A)=50.00 ± 24.50%	P(B)=37.50 ± 23.72%
		P(C)=12.50 ± 19.33%	P(D) - Not observed
		P(F) - Not observed	
	4	P(A)=50.00 ± 23.10%	P(B)=33.33 ± 21.78%
		P(C)=16.67 ± 19.99%	P(D) - Not observed
		P(F) - Not observed	
F200	3	P(A)=33.33 ± 46.05%	P(B)=50.00 ± 48.34%
		P(C)=16.67 ± 38.15%	P(D) - Not observed
		P(F) - Not observed	
	4	P(A)=33.33 ± 18.86%	P(B)=50.00 ± 20.00%
		P(C)=16.67 ± 19.99%	P(D) - Not observed
		P(F) - Not observed	

Table 2

Distribution of Grades, Means and Standard Deviations of CAPs of the 87 Actual Subjects

PLCC		YrsHSF 1	YrsHSF 2	YrsHSF 3	YrsHSF 4
	F100	A 0 B 1 C 1 D 0 F 0 N = 2 Mean=79.50 S.D.= 7.78	A 3 B 3 C 2 D 0 F 1 N = 9 Mean=82.67 S.D.=13.18	A 1 B 2 C 0 D 0 F 0 N = 3 Mean=88.33 S.D.= 6.11	A 2 B 1 C 0 D 1 F 0 N = 4 Mean=82.25 S.D.=15.22
	F150		A 1 B 3 C 1 D 0 F 0 N = 5 Mean=83.00 S.D.= 4.95	A 8 B 6 C 2 D 0 F 0 N = 16 Mean=88.06 S.D.= 6.02	A 9 B 6 C 3 D 0 F 0 N = 18 Mean=87.39 S.D.= 5.29
	F200			A 2 B 3 C 1 D 0 F 0 N = 6 Mean=84.50 S.D.= 7.48	A 8 B 12 C 4 D 0 F 0 N = 24 Mean=87.67 S.D.= 5.69

Regression equation:

CAP = 0.024868(PLCS) + 1.289194(YrHSF) + 70.542779
(Standard Error of Estimate = 7.37284)

Table 3

LMA-Predicted CAPs and 0.95 Confidence Intervals (C.I.) of Observed Mean CAPs of the 87 Actual Subjects

PLCC	PLCS Range	YrHSF	LMA-Predicted CAP Range	0.95 C.I. of Observed Mean CAP
F100	200 - 430	1	76.81 - 82.53	9.60 - 149.40[1] (2)
		2	84.06 - 84.81	72.54 - 92.80 (9)
		3	79.38 - 85.10	73.15 - 103.51[1] (3)
		4	80.67 - 86.39	58.03 - 106.47[1] (4)
F150	440 - 470	2	84.06 - 84.81	76.85 - 89.15 (5)
		3	85.35 - 86.10	84.85 - 91.27 (16)
		4	86.64 - 87.39	84.76 - 90.02 (18)
F200	480 - 520	3	86.35 - 87.34	76.65 - 92.35 (6)
		4	87.64 - 88.63	85.27 - 90.07 (24)

[1]For practical purposes, treat the upper bound as 100.

Note: The number in parenthesis in the last column is the number of students on which the confidence interval is based.

Table 4

Inter-correlation of CAP, PLCS, and YrHSF

(A) Actual Data Set (87 IU Subjects)

	CAP	PLCS	YrHSF
CAP	1.00	0.21 (p=.028)	0.21 (p=.024)
PLCS		1.00	0.55 (p=.000)
YrHSF			1.00

(p = one-tailed significance)

(B) Hypothetical Data Set (87 Hypothetical Subjects)

	CAP	PLCS	YrHSF
CAP	1.00	-0.04 (p=.360)	-0.12 (p=.126)
PLCS		1.00	0.53 (p=.000)
YrHSF			1.00

(p = one-tailed significance)

Table 5

APT and LMA-Predicted Probabilities of CAP Categories (Actual Data Set)

PLCC	YrHSF		CAP Category Probability A	B	C	D,F
F100	1	APT	0	0.5000	0.5000	0
		LMA	0.1131	0.4426	0.3762	0.0681
	2	APT	0.3333	0.3333	0.2222	0
		LMA	0.1539	0.4754	0.3242	0.0465
	3	APT	0.3333	0.6667	0	0
		LMA	0.2033	0.4952	0.2714	0.0301
	4	APT	0.5000	0.2500	0	0.2500
		LMA	0.2611	0.5000	0.2197	0.0192
F150	2	APT	0.2000	0.6000	0.2000	0
		LMA	0.2578	0.5033	0.2192	0.0197
	3	APT	0.5000	0.3750	0.1250	0
		LMA	0.3228	0.4931	0.1719	0.0122
	4	APT	0.5000	0.3333	0.1667	0
		LMA	0.3974	0.4647	0.1306	0.0073
F200	3	APT	0.3333	0.5000	0.1667	0
		LMA	0.2912	0.4969	0.1961	0.0158
	4	APT	0.3333	0.5000	0.1667	0
		LMA	0.3594	0.4795	0.1515	0.0096

Note: The LMA-predicted probabilities were based on the following regression equations:

CAP = 1.410342(YrHSF) + 79.640812 for PLCC F100
CAP = 1.410342(YrHSF) + 82.401424 for PLCC F150
CAP = 1.410342(YrHSF) + 81.674034 for PLCC F200
(Standard error of estimate = 7.39713)

Study 2

Method

A hypothetical data set was constructed in which CAP was not correlated with YrHSF nor with PLCS (see Table 4-B). In other words, the hypothetical data set was so constructed that it lacked linearity. Both the actual and the hypothetical data sets had the same number of subjects in each corresponding PLCC/YrHSF block. LMA and APT analyses were done on this hypothetical data set as in the first study.

Results

Tables 6, 7, 8, and 9 show the results of the APT and LMA analyses on the hypothetical data set. Note that the standard errors of estimate for the hypothetical data (Tables 7 and 9) were greater than those for the actual data from the 87 subjects (Tables 2 and 5). The greater standard errors of estimate were due to non-linearity in the hypothetical data.

As expected, LMA could not accurately describe the hypothetical data. For example, the mean CAP of the 16 hypothetical subjects who had 3 YrHSF and who were placed in F150 was 70.13 (see Table 7). The 0.95 confidence interval of CAP was 64.31 to 75.95 (see Table 8). However, the LMA-predicted CAP range was 81.68 to 82.02, which did not overlap with the confidence interval. In fact, five out of the nine confidence intervals in Table 8 deviated significantly from their corresponding LMA-predicted CAP ranges. All those confidence

intervals which did not deviate significantly from the LMA-predicted CAP ranges had small

Table 6

APT Probabilities (Hypothetical Data Set)

PLCC	YrHSF	APT Probability	
F100	1	P(A)=50.00 ± 94.30%	P(B)=50.00 ± 94.30%
		P(C) - Not observed	P(D) - Not observed
		P(F) - Not observed	
	2	P(A)=66.67 ± 36.35%	P(B)=33.33 ± 36.35%
		P(C) - Not observed	P(D) - Not observed
		P(F) - Not observed	
	3	P(A)=33.33 ± 70.01%	P(B)=66.67 ± 70.01%
		P(C) - Not observed	P(D) - Not observed
		P(F) - Not observed	
	4	P(A)=50.00 ± 61.50%	P(B)=50.00 ± 61.50%
		P(C) - Not observed	P(D) - Not observed
		P(F) - Not observed	
F150	2	P(A)=80.00 ± 45.06%	P(B) - Not observed
		P(C)=20.00 ± 45.06%	P(D) - Not observed
		P(F) - Not observed	
	3	P(A)= 6.25 ± 14.99%	P(B)= 6.25 ± 14.99%
		P(C)=43.75 ± 24.31%	P(D)=31.25 ± 25.84%
		P(F)=12.50 ± 19.33%	
	4	P(A)=11.11 ± 17.30%	P(B)= 5.56 ± 13.36%
		P(C)=27.78 ± 23.47%	P(D)=50.00 ± 23.10%
		P(F)= 5.56 ± 13.36%	
F200	3	P(A)=16.67 ± 38.15%	P(B) - Not observed
		P(C) - Not observed	P(D)=83.33 ± 38.15%
		P(F) - Not observed	
	4	P(A)=70.83 ± 18.18%	P(B)=25.00 ± 17.32%
		P(C) - Not observed	P(D) - Not observed
		P(F)= 4.17 ± 10.08%	

Table 7

Distribution of Grades, Means and Standard Deviations of CAPs of the 87 Hypothetical Subjects

PLCC	YrHSF 1	YrHSF 2	YrHSF 3	YrHSF 4
F100	A 1 B 1 C 0 D 0 F 0 N = 2 Mean=90.00 S.D.= 2.83	A 6 B 3 C 0 D 0 F 0 N = 9 Mean=92.67 S.D.= 4.24	A 1 B 2 C 0 D 0 F 0 N = 3 Mean=86.33 S.D.= 4.04	A 2 B 2 C 0 D 0 F 0 N = 4 Mean=90.75 S.D.= 7.54
F150		A 4 B 0 C 1 D 0 F 0 N = 5 Mean=91.60 S.D.=10.62	A 1 B 1 C 7 D 5 F 2 N = 16 Mean=70.13 S.D.=10.92	A 2 B 1 C 5 D 9 F 1 N = 18 Mean=69.17 S.D.=11.08
F200			A 1 B 0 C 0 D 5 F 0 N = 6 Mean=67.50 S.D.=11.35	A 17 B 6 C 0 D 0 F 1 N = 24 Mean=91.13 S.D.= 9.37

Regression equation:

CAP = 0.011264(PLCS) - 2.506426(YrHSF) + 84.244705
(Standard Error of Estimate = 14.40649)

Table 8

LMA-Predicted CAPs and 0.95 Confidence Intervals (C.I.) of Observed Mean CAPs of the 87 Hypothetical Subjects

PLCC	PLCS Range	YrHSF	LMA-Predicted CAP Range	0.95 C.I. of Observed Mean CAP
F100	200 - 430	1	83.99 - 86.58	64.57 - 115.43[1] (2)
		2	81.48 - 84.08	89.41 - 95.93* (9)
		3	78.98 - 81.57	76.29 - 96.37 (3)
		4	76.47 - 79.06	78.75 - 102.75[1] (4)
F150	440 - 470	2	84.19 - 84.53	78.42 - 104.78[1] (5)
		3	81.68 - 82.02	64.31 - 75.95* (16)
		4	79.18 - 79.51	63.66 - 74.68* (18)
F200	480 - 520	3	82.13 - 82.58	55.59 - 79.41* (6)
		4	79.63 - 80.08	87.17 - 95.09* (24)

*Significant
[1]For practical purposes, treat the upper bound as 100.

Note: The number in parenthesis in the last column is the number of students on which the confidence interval is based.

Table 9

APT and LMA-Predicted Probabilities of CAP Categories (Hypothetical Data Set)

PLCC	YrHSF		CAP Category Probability A	B	C	D,F
F100	1	APT	0.5000	0.5000	0	0
		LMA	0.5948	0.2629	0.1129	0.0294
	2	APT	0.6667	0.3333	0	0
		LMA	0.5517	0.2798	0.1310	0.0375
	3	APT	0.3333	0.6667	0	0
		LMA	0.5080	0.2915	0.1530	0.0475
	4	APT	0.5000	0.5000	0	0
		LMA	0.4641	0.3032	0.1733	0.0594
F150	2	APT*	0.8000	0	0.2000	0
		LMA*	0.0968	0.2188	0.3212	0.3632
	3	APT	0.0625	0.0625	0.4375	0.4375
		LMA	0.0793	0.1983	0.3172	0.4052
	4	APT	0.1111	0.0556	0.2778	0.5556
		LMA	0.0630	0.1790	0.3097	0.4483
F200	3	APT*	0.1667	0	0	0.8333
		LMA*	0.4168	0.3156	0.1927	0.0749
	4	APT*	0.7083	0.2500	0	0.0417
		LMA*	0.3745	0.3205	0.2132	0.0918

*Significant at the 0.05 level

Note: The LMA-predicted probabilities were based on the following regression equations:

CAP = -1.357798(YrHSF) + 94.283384 for PLCC F100
CAP = -1.357798(YrHSF) + 76.961891 for PLCC F150
CAP = -1.357798(YrHSF) + 91.559633 for PLCC F200
(Standard error of estimate = 12.10242)

sample sizes. Had those sample sizes been larger, the confidence intervals would have been narrower and more instances of statistically significant deviation might have been observed.

Table 9 shows the observed APT probabilities and LMA-predicted probabilities of different CAP categories for the hypothetical data set. The X^2 goodness-of-fit test was applied and significant differences between APT and LMA-predicted probabilities were found for three PLCC/YrHSF blocks. This demonstrated the inadequacy of LMA in analyzing non-linear data.

Results from this study show that if linearity is absent in the data, it is necessary to describe the data at different levels of various variables. APT describes what has actually occurred under various situations and so was a more appropriate tool for analyzing the hypothetical data.

Discussion

On the basis of the results from the two studies reported in this paper, APT appears to be a more powerful tool than LMA in analyzing data with no inherent linear or deterministic relations. APT probabilities retain more specific information in the data by not averaging data across levels of various variables, as in LMA. It is thus a better tool for analyzing stochastic educational processes.

The French placement data in the first study were collected with LMA as the intended method of analysis. The data did not allow APT analyses in terms of relative duration. Thus, results from the present studies cannot be considered as a "complete"

illustration of the APT model. Though the data sets used in the two studies demonstrated the appropriateness of using APT to analyze non-linear relations, they did not demonstrate a very important component of APT, which is temporal sequencing. Temporal sequencing information in the data is necessary to reveal temporal patterns of occurrences of events.

The present authors have no intention in this paper of comparing APT with various statistical models. However, one reviewer who read the proposal for this paper mentioned comparing APT with the Markov model. The Markov model is, in essence, concerned with the probability of being in one of a group of mutually exclusive and collectively exhaustive states at some future time, given an initial probability state vector and a matrix of transitional probabilities between the various states (Hudson and Bruno, 1978).

It is noteworthy to point out here that Frick (in press) has compared APT with different extant methodologies, including the Markov model, various event history analysis models, and LMA variations like time series analysis, path analysis, discriminant analysis, and so on. Frick noted two differences between APT and the Markov model. First, APT permits investigation of temporal patterns which are longer than two-stage sequences. Second, it is possible to consider simultaneously multiple classifications in APT, whereas in the Markov model, only one is considered. However, Frick also noted that if there is only one

classification of interest, then APT bears some resemblance to the Markov model.

The same reviewer mentioned above also suggested proposing a general approach to using stochastic models for solving educational measurement problems. Bayesian reasoning can lay the groundwork of such a general approach. By Bayesian reasoning, it is meant here that some pre-determined or observed prior probabilities are used at the occurrence of a certain event of interest to determine corresponding posterior probabilities. The posterior probabilities are then used as prior probabilities at the next occurrence of the event and new posterior probabilities are then estimated.

Bayesian or Bayesian-like updating of observed APT probabilities and relative duration measures can be proposed as a general system approach to educational measurement, particularly with respect to adaptive testing and adaptive instruction. It has been demonstrated that Bayesian reasoning is very useful in adaptive testing (Frick, 1989; Frick, Plew, & Luk, 1989). Bayesian use of APT measures can result in an improvement of a system by revealing existing yet previously unknown temporal paths. It can also improve the system's knowledge of how probable various events will occur, on the basis of past experiences. In a general sense, this means an "intelligent" system that can "learn" from past patterns.

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